CS190C Lec5

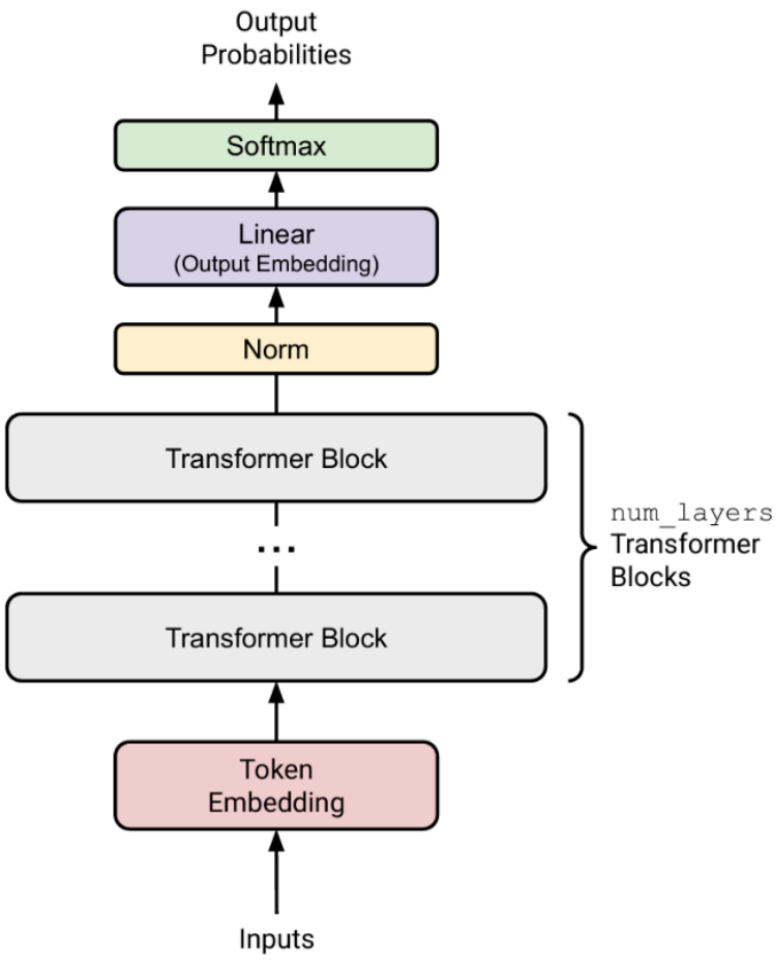
Build Transformer

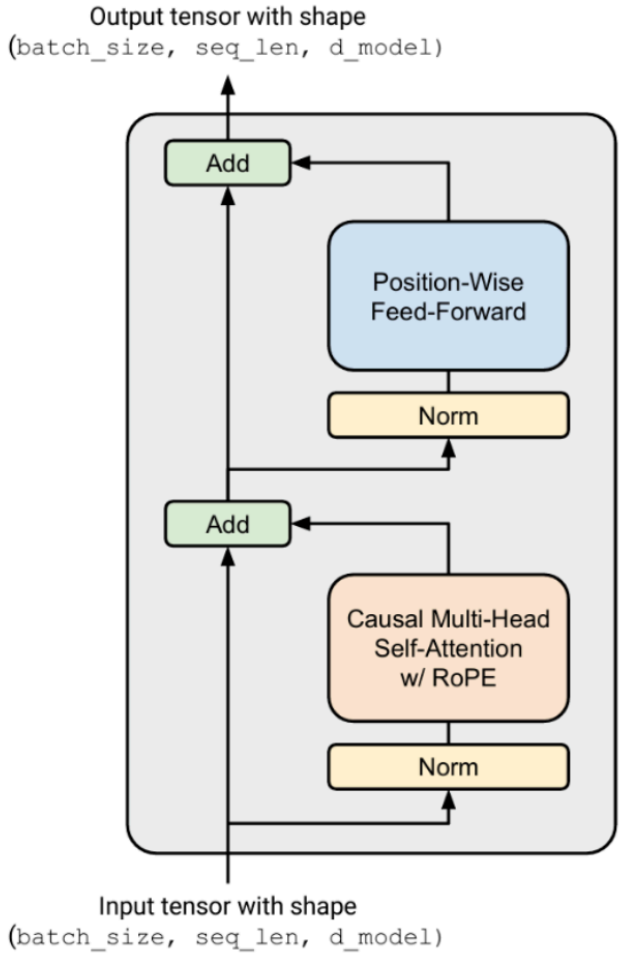
Overview

- Macro System Architecture
- Code Implementation of Basic Computational Components
- Code Implementation of RoPE
- Code Implementation of FFN and Attention
- Assembly of Transformer Block and Final Model

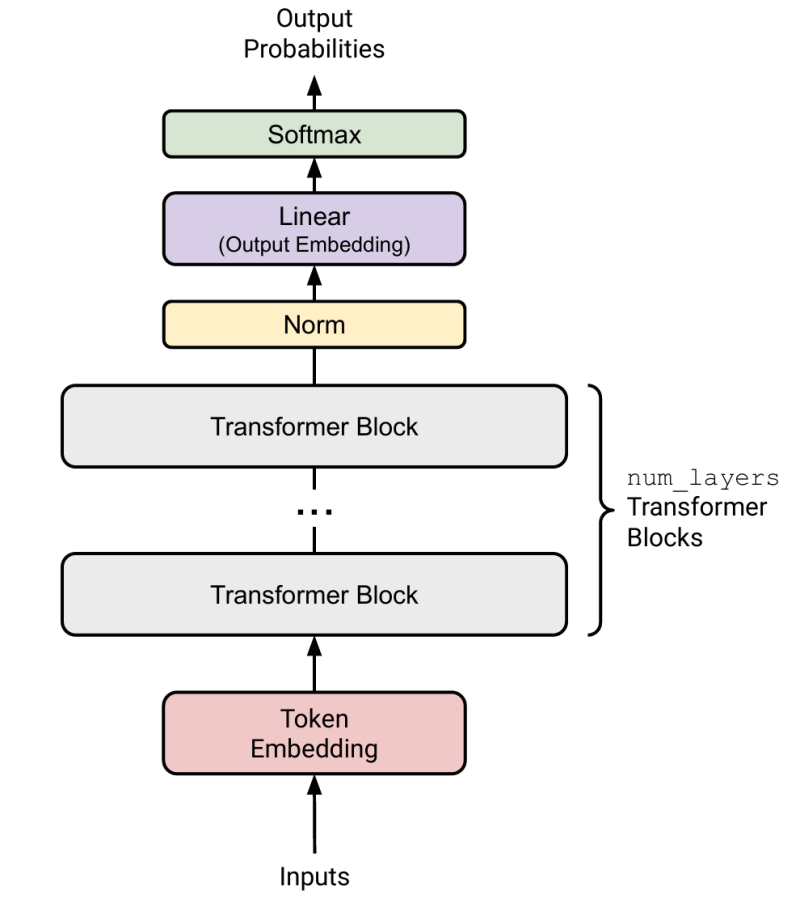
PART1: Macro System Architecture

Transformer Overall Architecture Diagram



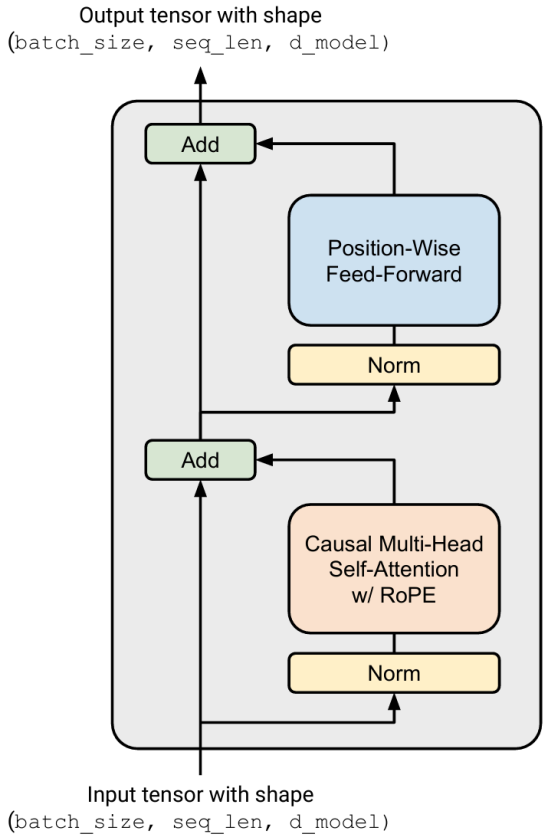


Modules of the whole Transformer



- Pass through a `Token Embedding` module to turn to dense vector (Input layer)
- Pass through several `Transformer Block` modules to absorb information in multiple rounds (Hidden layer)
- Normalize the number scale of final tensor
- Linear transform, calculate possible scores for generating of each word (Output layer)

Modules of each Transformer Block

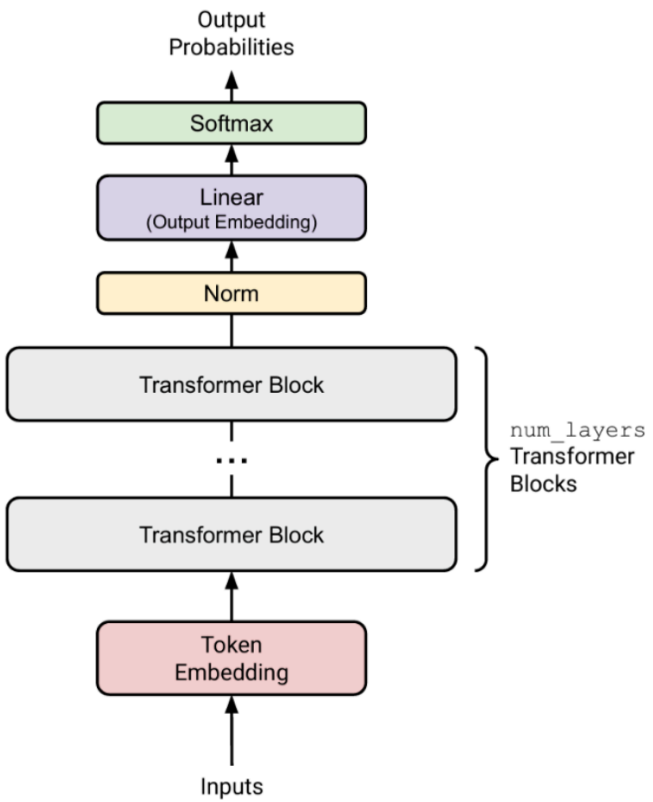


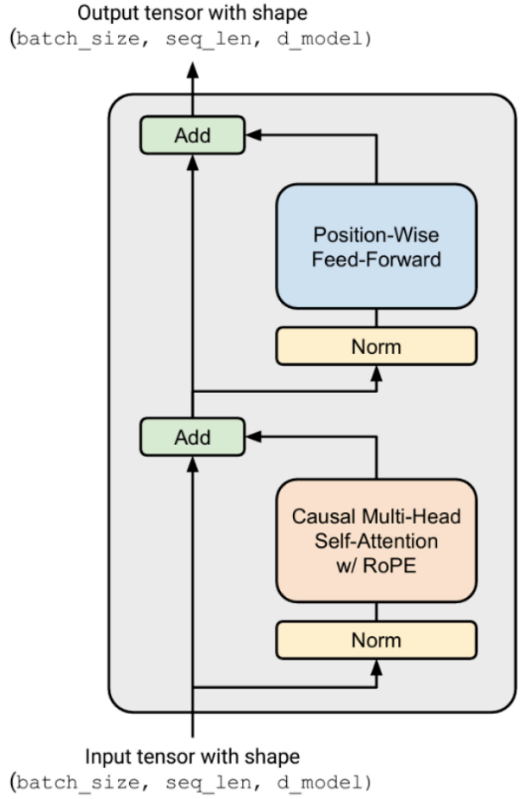
- Pre-layer RMSNorm module
- MHA Module with Residual Connection
  - contains RoPE module if position embedding needed
  - contains Softmax module for calculation of attention score
- Pre-layer RMSNorm module
- FFN Module with Residual Connection
  - contains SiLU module

Moreover, almost all modules require calling the **linear transformation** module!

PART2: Code Implementation of Basic Computational Components

Basic Components to be Implemented





Modules to be implemented:

- `Token Embedding`
- `Linear`
- `RMSNorm`
- `SiLU`
- `Softmax`

1. `class Generate_Embeddings`

IDEA:

- Most original input: BPE encoding results (e.g., `[3,10,2,6,4]`, all token IDs from the vocabulary)
- Tensor shape: `[batch_size, seq_len]`
- Expected model input: Different words in the vocabulary have different embedding vectors $\mathrm{emb}_i \in R^{d\_model}$
- Implementation idea:
  - Generate a learnable matrix $W_e \in R^{|V|*d\_model}$.
  - The i-th column represents emb_i
  - Randomly initialized W_e, representing no prior knowledge about the meaning of any word at first.
  - Learn W_e with other parameters during the training process.

1. `class Generate_Embeddings`

Parameter scheme:

- Initialization phase: Pass in `vocab_size`, `d_model`, `device` (the device where PyTorch tensors are stored), and `dtype` (numerical type of tensor elements).
- Forward phase:
  - Pass in `token_ids` (shape `[batch_size, seq_len]`)
  - Output shape is `[batch_size, seq_len, d_model]`

1. `class Generate_Embeddings`

```
# vocab_size*embedding_dim矩阵中取样
class Generate_Embeddings(nn.Module):

    def __init__(self,number_embeddings:int,embedding_dim:int,device=None,dtype=None):
        super(Generate_Embeddings,self).__init__()
        self.embedding_matrix=torch.empty(number_embeddings,
                                          embedding_dim,
                                          device=device,
                                          dtype=torch.float32)
        nn.init.trunc_normal_(self.embedding_matrix,mean=0,std=0.02)

    def forward(self,token_ids:torch.Tensor)->torch.Tensor:
        return self.embedding_matrix[token_ids]
```

2. `class Linear_Transform`

IDEA:

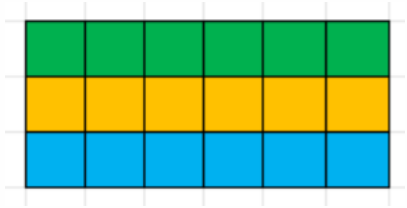
- Assume we need to transform a 3-dimensional tensor into a 6-dimensional one...
- Mathematically speaking: Let the 3D tensor `x` $(1 * 3)$ right-multiply a $3 * 6$ matrix `W`
- The shape of `xW` is then $1 * 6$, just like the diagram below.

Question: Linear operations are the most frequent in LLMs……

Can this operation be accelerated as much as possible?

2. `class Linear_Transform`

- PyTorch tensors follow the "last dimension elements have contiguous memory addresses" principle.
- For a $3 * 6$ tensor W, its memory layout as the diagram(same color means contiguous):



- For a $4 * 3 * 6$ tensor (`[batch size, rows, columns]`), every 6 elements are also contiguous (e.g., the memory address difference between `[1,1,1]` and `[1,1,2]` is 1 units, and the memory address difference between `[1,1,1]` and `[1,2,1]` is 6 units).
- That is: Matrix elements in the same row have contiguous memory, while those in the same column do not $\Rightarrow$ **Row-major order principle**.

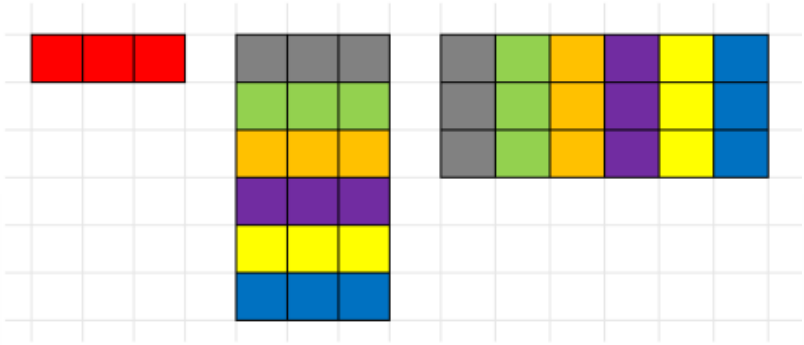
2. `class Linear_Transform`

Perform 6 vector dot product operations. In each operation:

- `x` participates as a whole row, memory is contiguous, can fully utilize cache
- `W` participates as a whole column, memory is not contiguous, may not utilize cache effectively

How can we make `W` also participate "as a whole row" in each operation?

2. `class Linear_Transform`



- PyTorch's transpose operation does not change the tensor's underlying memory space, just change stepsize. (Can you give an example?)
- Create new `W`: `[6,3]` (every 3 elements are contiguous in memory)
- Transpose `W` to `[3,6]`: Can perform matrix multiplication, and the memory distribution remains unchanged
- `x` and `W` have fully contiguous memory access during each operation, allowing full utilization of cache!

2. `class Linear_Transform`

```
# 重点：行主序规则
class Linear_Transform(nn.Module):

    def __init__(self,in_features:int,out_features:int,device=None,dtype=None):
        super(Linear_Transform,self).__init__()
        self.linear_matrix=torch.empty(out_features,
                                       in_features,
                                       device=device,
                                       dtype=torch.float32)

        self.linear_matrix=self.linear_matrix.transpose(-2,-1)
        nn.init.trunc_normal_(self.linear_matrix,mean=0,std=0.02)
        self.linear_matrix=nn.Parameter(self.linear_matrix)

    def forward(self,x:torch.Tensor)->torch.Tensor:
        return torch.matmul(x,self.linear_matrix)
```

3. `class RMSNorm`

IDEA: Normalize the input tensor $\vec{a}$ (We've discussed why at `Lec3`)

- $a_i = \frac{a_i}{RMS(\vec{a})} g_i$ (divide by normalization weight uniformly, and apply learnable fine-tuning)
- g_i is a learnable parameter
- $RMS(\vec{a}) = \sqrt{(\frac{1}{d_{model}} \sum a_i^2) + \epsilon}$, that is L2-Norm.

Input tensor shape: `[batch_size, seq_len, d_model]` $\Rightarrow$ Not a 1D vector, how to handle?

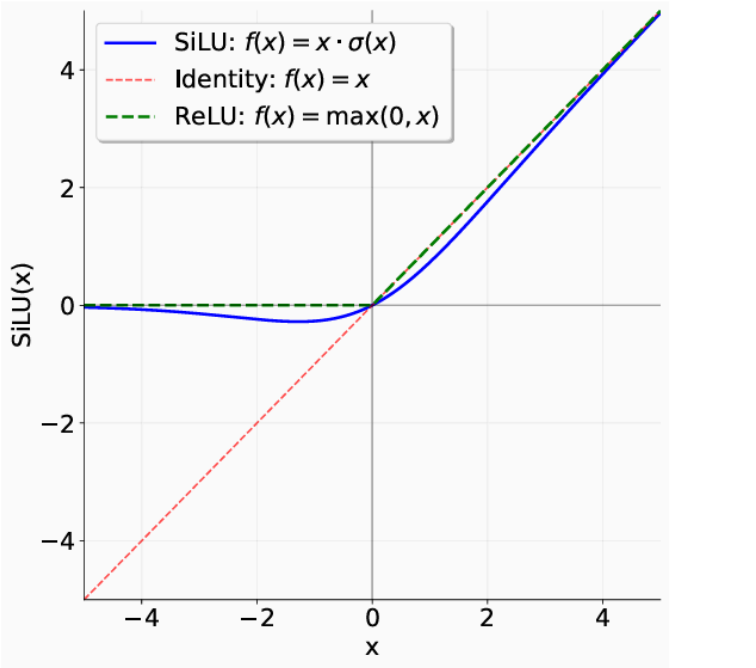
PyTorch's broadcasting mechanism:

- Operations are performed on the last few dimensions by default, previous dimensions are all replication operations
- Equivalent to parallel operations on `batch_size * seq_len` parallel `d_model` -dimensional tensors.
- Just process it as 1D vector `[d_model]` !

3. `class RMSNorm`

```python
# 运算法则：归一化*可学习缩放倍数
class RMSNorm(nn.Module):
    def __init__(self,d_model:int,eps:float=1e-5,device=None,dtype=None):
        super(RMSNorm,self).__init__()
        self.eps=eps
        self.g=nn.Parameter(torch.ones(d_model,device=device,dtype=torch.float32))

    def _get_rms(self,x:torch.Tensor)->torch.Tensor:
        sum_square=torch.sum(x**2,dim=-1,keepdim=True)
        mean_square=sum_square/x.shape[-1]
        return torch.sqrt(mean_square+self.eps)

    def forward(self,x:torch.Tensor)->torch.Tensor:
        ori_dtype=x.dtype
        x=x.to(torch.float32) # 张量元素类型转换，确保运算精度
        rms=self._get_rms(x)
        x_normed=x/rms
        x_normed=x_normed.to(ori_dtype) # 张量元素类型还原
        return x_normed*self.g
```

4. `class SiLU_Activation`



$\text{SiLU}: f(x) = x \cdot \sigma(x)$
$\text{ReLU}: f(x) = \max(0, x)$

- For $x < 0$: roughly equals to 0
- For $x > 0$: roughly stays the same
- Compare with ReLU: smooth and differentiable at $x = 0$

4. `class SiLU_Activation`

```
class Sigmoid_Activation(nn.Module):
    def __init__(self):
        super(Sigmoid_Activation,self).__init__()

    def forward(self,x:torch.Tensor)->torch.Tensor:
        denominator=1+torch.exp(-x)
        return 1/denominator

class SiLU_Activation(nn.Module):
    def __init__(self):
        super(SiLU_Activation,self).__init__()
        self.sigmoid_activator=Sigmoid_Activation()

    def forward(self,x:torch.Tensor)->torch.Tensor:
        sigmoid_x=self.sigmoid_activator(x)
        return x*sigmoid_x
```

5. `class Softmax_Activation`

How to turn a score tensor to a distribution?

$$x_i = \frac{e^{x_i}}{\sum e^{x_i}}$$

- Each x_i calculates its exponential as a weight, then performs weight normalization
- Can make the advantage of relatively larger values more pronounced
- Even smaller values remain non-zero after normalization

Problem: What if there exists a very large x_i? (e.g., normalizing `[20,3,1005]`)

- e^{1000} = `NAN`

5. `class Softmax_Activation`

- Normalizing `[100,101,102]` vs Normalizing `[-2,-1,0]`
- Weight of 102: $\frac{e^{102}}{e^{102}+e^{101}+e^{100}} = \frac{e^{0}}{e^{0}+e^{-1}+e^{-2}}$
- The Softmax normalization result of `[100,101,102]` is equivalent to that of `[-2,-1,0]`

Let x_{max} be the maximum value among x_i:

$$\mathrm{Softmax}(x_i) = \frac{e^{x_i}}{\sum e^{x_i}}$$

$$= \frac{e^{x_i}/e^{x_{max}}}{\sum e^{x_i}/e^{x_{max}}}$$

$$= \frac{e^{x_i - x_{max}}}{\sum e^{x_i - x_{max}}}$$

That is: subtract x_{max} from all x_i to avoid problems with extremely large values that cannot be calculated!

5. `class Softmax_Activation`

```
class Softmax_Activation(nn.Module):
    def __init__(self,dim:int=-1):
        super(Softmax_Activation,self).__init__()
        self.dim=dim

    def forward(self,x:torch.Tensor)->torch.Tensor:
        #shape of x:(bsz,seq_len,d_k)
        x_max=torch.max(x,dim=self.dim,keepdim=True).values
        x_exp=torch.exp(x-x_max)
        x_exp_sum=torch.sum(x_exp,dim=self.dim,keepdim=True)
        return x_exp/x_exp_sum
```

`x_max`：`[bsz, seq_len]`，`x`：`[bsz,seq_len,d_k]`.

`x-x_max` exhibits another type of broadcasting mechanism: replication operation

PART3: Code Implementation of RoPE

Review: RoPE Calculation Rules

$\vec{x} \Rightarrow R_i\vec{x}$ ($\vec{x} \in R^d$,d is even)

Divide the d-dimensional vector into several sub-segments of length 2, resulting in a total of $d/2$ sub-segments, each sub-segment makes a rotation of angle $\theta_{i,k}$.
(Proportional to position i)

$$R^i = \begin{bmatrix} R_1^i & 0 & 0 & \cdots & 0 \\ 0 & R_2^i & 0 & \cdots & 0 \\ 0 & 0 & R_3^i & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & R_{d/2}^i \end{bmatrix} \quad R_k^i = \begin{bmatrix} \cos(\theta_{i,k}) & -\sin(\theta_{i,k}) \\ \sin(\theta_{i,k}) & \cos(\theta_{i,k}) \end{bmatrix}.$$

where $\theta_{i,k} = \frac{i}{\Theta^{2k/d}}$

Review: RoPE Calculation Rules

$$R^i = \begin{bmatrix} R_1^i & 0 & 0 & \cdots & 0 \\ 0 & R_2^i & 0 & \cdots & 0 \\ 0 & 0 & R_3^i & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & R_{d/2}^i \end{bmatrix} \quad R_k^i = \begin{bmatrix} \cos(\theta_{i,k}) & -\sin(\theta_{i,k}) \\ \sin(\theta_{i,k}) & \cos(\theta_{i,k}) \end{bmatrix}.$$

Property of matrix R : $(R^m)^T R^n = R^{n-m}$

In the attention mechanism, for the query vector q_i at position i and the key vector k_j at position j :

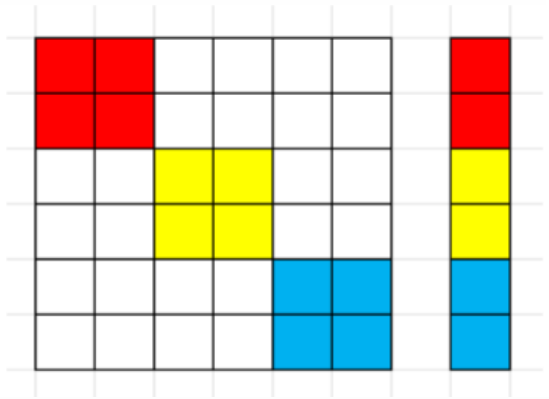
- $q_i' = R^i q_i,\ k_j' = R^j k_j$
- $q_i'^T k_j' = q_i^T (R^i)^T R^j k_j = q_i^T R^{j-i} k_j$

The transformation caused by position, is only related to relative position.

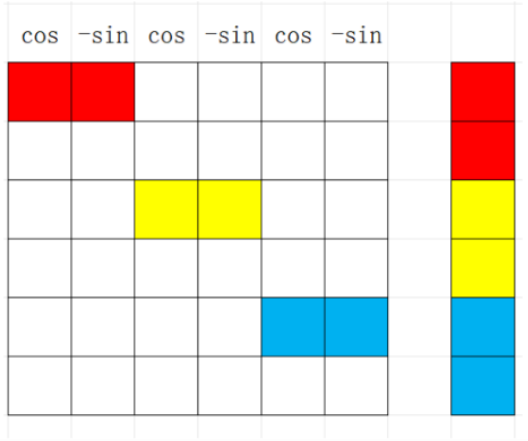
How to Avoid Brute-force Matrix Multiplication?

- Observation: Even rows of the matrix correspond to the same transformation rule: `[cos, -sin]`, with angle $\theta_{i,k}$ as the variable
- If these even rows sharing the same rule can be computed efficiently in a unified manner, how should subsequent processing proceed?

$$R^i = \begin{bmatrix} R_1^i & 0 & 0 & \cdots & 0 \\ 0 & R_2^i & 0 & \cdots & 0 \\ 0 & 0 & R_3^i & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & R_{d/2}^i \end{bmatrix}$$

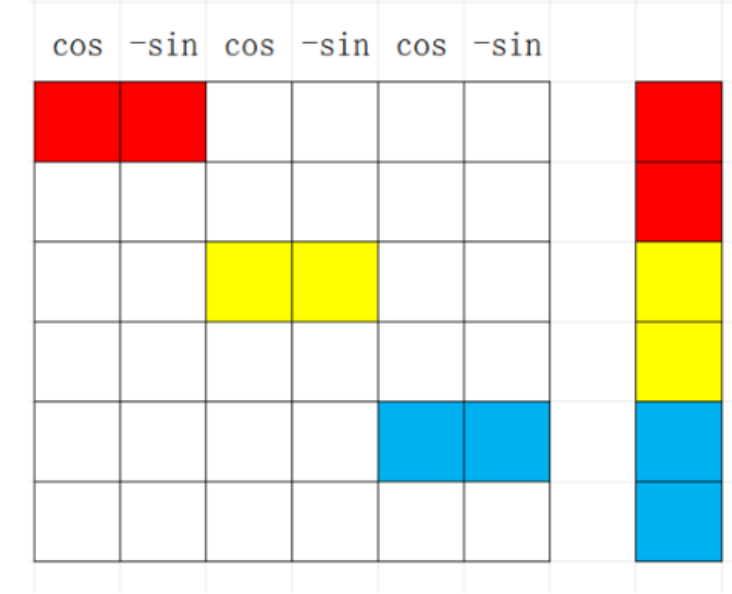


$$R_k^i = \begin{bmatrix} \cos(\theta_{i,k}) & -\sin(\theta_{i,k}) \\ \sin(\theta_{i,k}) & \cos(\theta_{i,k}) \end{bmatrix}.$$



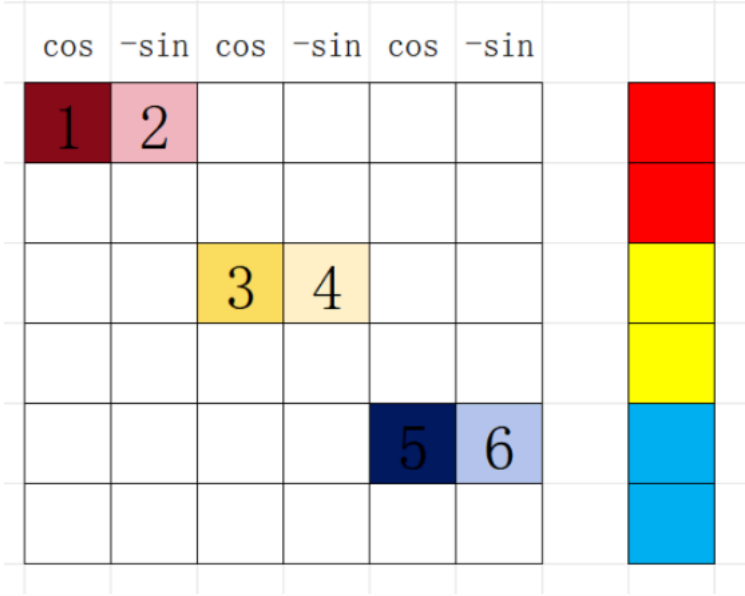
How to Avoid Brute-force Matrix Multiplication?

- Calculate products of `Red-Red`, `Yellow-Yellow`, `Blue-Blue`, which coreespond to: x_0, x_2, x_4 after RoPE
- x_1, x_3, x_5 are the same.
- Calculate each 2-number blocks, and calculate products.



How to Calculate 2-number blocks of R_i?

- Pre-calculate a $\theta_{i,k}$ lookup table of size `[max_seq_len, d/2]`
- Then calculate lookup tables of the same size for $cos(\theta_{i,k})$ and $sin(\theta_{i,k})$
- Obtain values at positions 1, 3, 5 directly from the cos lookup table
- Obtain values at positions 2, 4, 6 directly from the sin lookup table



How to Calculate 2-number blocks of R_i?

- Concatenate pairs 12, 34, 56 into 3 blocks, perform block-wise dot product with the 3 blocks of `x`, obtaining the values for the three even rows.
- Similarly, obtain the values for all odd rows of the transformed `x`, concatenate both to get the complete transformed `x` vector.

Code Implementation of RoPE

```
class RoPE(nn.Module):
    def __init__(self,theta:float,d_k:int,max_seq_len:int,device=None):
        super(RoPE,self).__init__()
        self.theta=theta
        self.d_k=d_k
        self.max_seq_len=max_seq_len
        self.device=device

        d_half=d_k//2
        positions=torch.arange(max_seq_len, device=device).unsqueeze(1)#[max_seq_len,1]
        dims=torch.arange(d_half,device=device).unsqueeze(0)#[1,d_half]
        angles=positions/(theta**(2*dims/d_k))#[max_seq_len,d_half]

        cos_values=torch.cos(angles).unsqueeze(0)
        self.register_buffer("cos_values",cos_values)#(1,max_seq_len,d_half)
        sin_values=torch.sin(angles).unsqueeze(0)
        self.register_buffer("sin_values",sin_values)#(1,max_seq_len,d_half)
```

`max_seq_len` : maximum iteration value of i; `angles` : values of $\theta_{i,k}$

`positions` : sequence of i values; `dims` : sequence of k values;

Division of angles is element-wise

Code Implementation of RoPE

```
def forward(self,x:torch.Tensor,token_positions:torch.Tensor)->torch.Tensor:
    x_splited=x.reshape(*x.shape[:-1],self.d_k//2,2)
    cos_chunk=self.cos_values[:,token_positions,:]
    sin_chunk=self.sin_values[:,token_positions,:]

    even_transform=torch.stack([cos_chunk,-sin_chunk],dim=-1)
    odd_transform=torch.stack([sin_chunk,cos_chunk],dim=-1)

    x_rotated_odd=torch.sum(x_splited*even_transform,dim=-1)#(bsz,seq_len,d_k//2)
    x_rotated_even=torch.sum(x_splited*odd_transform,dim=-1)#(bsz,seq_len,d_k//2)
    stacked_x=torch.stack([x_rotated_odd,x_rotated_even],dim=-1)
    x_rotated=stacked_x.reshape(*stacked_x.shape[:-2],self.d_k)

    return x_rotated
```

`cos_chunk` : `d_half` dimensional lookup table for each i position (positions 1, 3, 5)

PART4: Code Implementation of FFN and Attention

1. `class Feed_Forward_Network`

Module algorithm (excluding residual connection):

- Input tensor `x` (`d_model` dimensional)
- Route 1: Transform via `W1` to `d_ff` dimensional, pass through `SiLU` activation function to get new `x`
- Route 2: Transform via `W3` for another expansion, getting gated `d_ff` dimensional
- Element-wise multiplication of `x` and gated, getting new `x`
- Transform back to `d_model` dimensional via `W2`

We call it `SwiGLU`:$\mathrm{FFN}(x) = \mathrm{SwiGLU}(x, W_1, W_2, W_3)$

1. `class Feed_Forward_Network`

```
class Feed_Forward_Network(nn.Module):
    def __init__(self,
                 d_model:int,
                 d_ff=None,
                 device=None,
                 dtype=None):
        super(Feed_Forward_Network,self).__init__()

        self.d_model=d_model
        if d_ff is not None:
            self.d_ff=d_ff
        else:
            self.d_ff=int(8/3*d_model)

        self.linear_w1=Linear_Transform(d_model,d_ff,device=device,dtype=dtype)
        self.linear_w3=Linear_Transform(d_model,d_ff,device=device,dtype=dtype)
        self.linear_w2=Linear_Transform(d_ff,d_model,device=device,dtype=dtype)
        self.activator=SiLU_Activation()
```

1. `class Feed_Forward_Network`

```
def forward(self,x:torch.Tensor)->torch.Tensor:
    enhanced=self.linear_w1(x)
    activated=self.activator(enhanced)
    gate=self.linear_w3(x)
    gated=activated*gate
    output=self.linear_w2(gated)
    return output
```

2. `class Multihead_Attention`

Module algorithm (excluding residual connection):

- Input tensor `x` with size `[batch_size, seq_len, d_model]`
- Through three linear transformations, essentially linearly transforming each d_model dimensional word vector of x to get:
  - `Q`, `K` matrices `[batch_size, seq_len, num_heads*d_k]`
  - `V` matrix `[batch_size, seq_len, num_heads*d_v]`
- Perform `RoPE` positional encoding on `Q`, `K` matrices
- Generate attention upper triangular mask (to prevent breaking the "autoregressive" assumption)
- Use QKV matrices and attention mask to compute attention output

2. `class Multihead_Attention`

Method for calculating attention output:

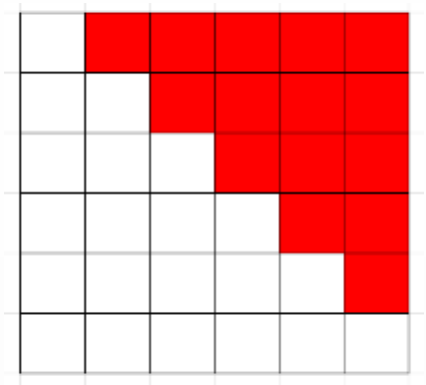
- Multiply `Q`, `K` matrices to calculate token feature matching scores
- Apply mask processing to the matching score matrix
- $\mathrm{Softmax}(\frac{QK^T}{\sqrt{d_k}})$, calculate attention scores between tokens
- Multiply the score matrix by the `V` matrix to get the attention output of each head
- Multiply `W_O` matrix to integrate heads

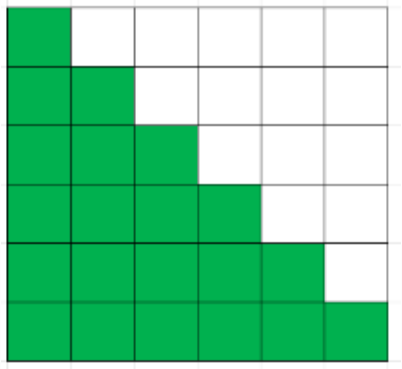
Calculation of Attention Output for One Head

```
class Scaled_dot_Product_Attention(nn.Module):
    def __init__(self):
        super(Scaled_dot_Product_Attention,self).__init__()

    def forward(self,Q:torch.Tensor,K:torch.Tensor,V:torch.Tensor,mask:torch.Tensor=None)->torch.Tensor:
        d_k=Q.shape[-1]

        attn_score=torch.matmul(Q,K.transpose(-2,-1))/math.sqrt(d_k)#[bsz,*,Qseq_len,Kseq_len]
        if mask is not None:
            attn_score=attn_score.masked_fill(mask==0,float('-inf'))
        softmax=Softmax_Activation(dim=-1)
        attn_weight=softmax(attn_score)#[bsz,*,Qseq_len,Kseq_len]

        #V:[bsz,*,Kseq_len,d_v]
        attn_output=torch.matmul(attn_weight,V)
        return attn_output#[bsz,*,Qseq_len,d_v]
```

Generation of Attention Mask

```
class Causal_Mask:
    def __init__(self,seq_len,device=None):
        self.seq_len=seq_len
        self.device=device

    def generate(self)->torch.Tensor:
        ones=torch.ones(self.seq_len,self.seq_len,device=self.device)
        mask=torch.triu(ones,diagonal=1)
        mask=(mask==0)
        return mask
```





`triu` : retains elements above the main diagonal and the diagonal starting from the 'diagonal' index

List of Sub-modules in Multihead_Attention

- Attention mask generation module
- Attention output calculation module (sdpa)
- RoPE module $\Rightarrow$ Requires additional parameters like max_seq_len, theta, token_positions, etc.
- Four types of linear transformations: Q, K, V, O

Assembly of Complete Module

```
class Multihead_Attention(nn.Module):
    def __init__(self,
                 d_model:int,
                 num_heads:int,
                 max_seq_length:int=None,
                 theta:int=None,
                 device=None):
        super(Multihead_Attention,self).__init__()

        self.d_model=d_model
        self.num_heads=num_heads
        self.d_k=d_model//num_heads
        self.d_v=d_model//num_heads

        self.max_seq_length=max_seq_length
        self.theta=theta
        self.token_positions=None

        self.q_proj=Linear_Transform(d_model,num_heads*self.d_k,device=device)
        self.k_proj=Linear_Transform(d_model,num_heads*self.d_k,device=device)
        self.v_proj=Linear_Transform(d_model,num_heads*self.d_v,device=device)
        self.o_proj=Linear_Transform(num_heads*self.d_v,d_model,device=device)

        self.sdpa=Scaled_dot_Product_Attention()

        if max_seq_length is not None and theta is not None:
            self.rope=RoPE(theta,self.d_k,max_seq_length,device=device)
        else:
            self.rope=None
```

Assembly of Complete Module

```
def forward(self,x:torch.Tensor,token_positions:torch.Tensor=None)->torch.Tensor:
    bsz=x.shape[0]
    seq_len=x.shape[1]

    #qk:[bsz,n_heads,seq_len,d_k]
    #v:[bsz,n_heads,seq_len,d_v]
    Q=self.q_proj(x)
    Q=Q.reshape(bsz,seq_len,self.num_heads,self.d_k).transpose(1,2)
    K=self.k_proj(x)
    K=K.reshape(bsz,seq_len,self.num_heads,self.d_k).transpose(1,2)
    V=self.v_proj(x)
    V=V.reshape(bsz,seq_len,self.num_heads,self.d_v).transpose(1,2)

    #apply RoPE on QK
    if self.rope is not None:
        self.token_positions=token_positions
        Q=self.rope(Q,self.token_positions)
        K=self.rope(K,self.token_positions)
```

Assembly of Complete Module

```
mask=Causal_Mask(seq_len,device=x.device).generate()
mask=mask.unsqueeze(0).unsqueeze(1)

attn_output=self.sdpa(Q,K,V,mask)
attn_output=attn_output.transpose(1,2).reshape(bsz,seq_len,self.num_heads*self.d_v)
attn_output=self.o_proj(attn_output)

return attn_output
```

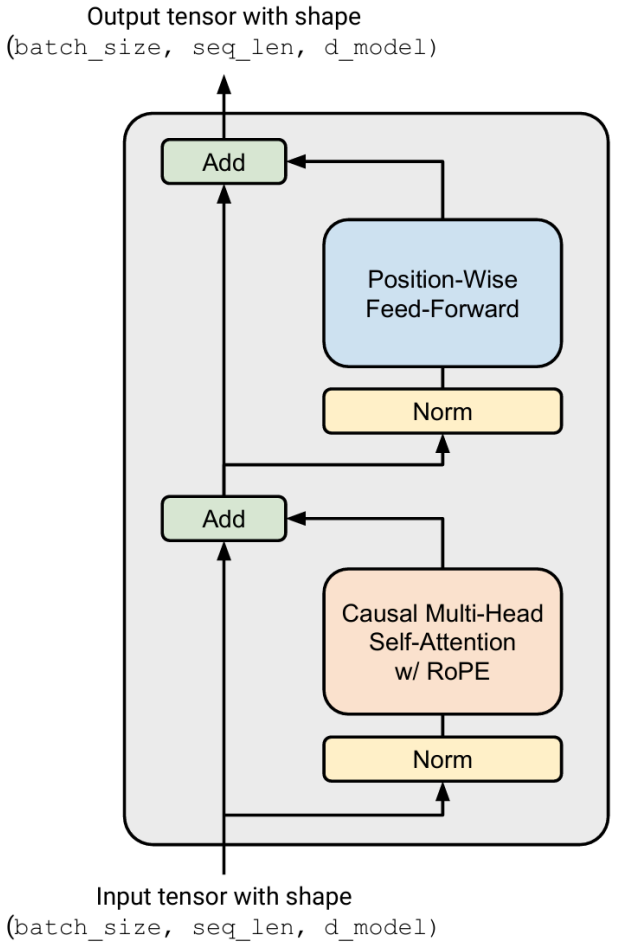
Original attn_output: `[bsz, num_heads, seq_len, d_v]`

`[bsz, seq_len, num_heads, d_v]` $\Rightarrow$ `[bsz, seq_len, num_heads*d_v]`

Final shape: `[bsz, seq_len, d_model]`

PART5: Assembly of Transformer Block and Final Model

Structure of Transformer Block



- A RMSNorm module
- A MHA module
- Residual connection
- An other RMSNorm module
- A FFN module
- Residual connection

The parameters received by each Block are the union of all parameters required by the above modules!

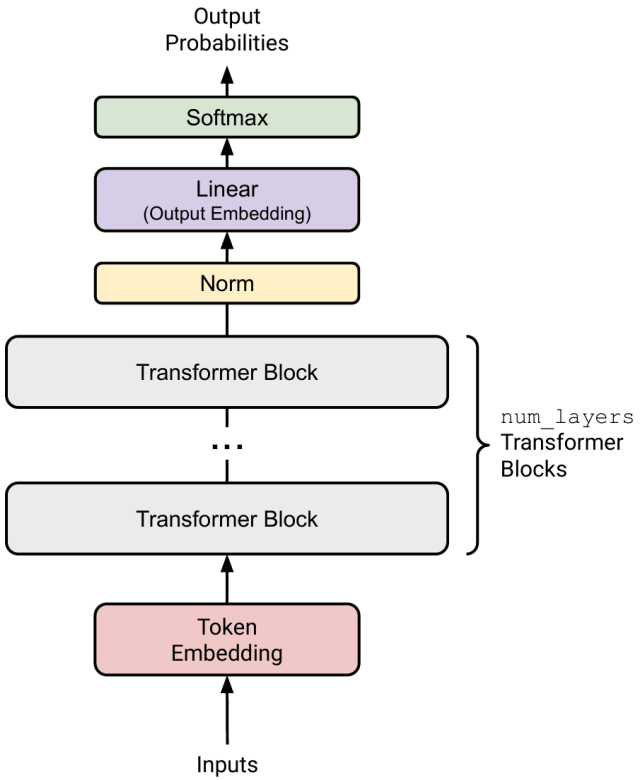
Assembly of Transformer Block

```
class Transformer_Block(nn.Module):
    def __init__(self,
                 d_model:int,
                 num_heads:int,
                 d_ff:int,
                 max_seq_length:int=None,
                 theta:int=None,
                 dtype=None,
                 device=None):
        super(Transformer_Block,self).__init__()
        self.RMSNorm_Attn=RMSNorm(d_model,dtype=dtype,device=device)
        self.RMSNorm_FF=RMSNorm(d_model,dtype=dtype,device=device)
        self.Multihead_Attn=Multihead_Attention(d_model,num_heads,max_seq_length,theta,device=device)
        self.Feed_Forward=Feed_Forward_Network(d_model,d_ff,device=device,dtype=dtype)
```

Assembly of Transformer Block

```
def forward(self,x:torch.Tensor,token_positions:torch.Tensor)->torch.Tensor:
    residual_attn=x
    x_normed_attn=self.RMSNorm_Attn(x)
    attn_output=self.Multihead_Attn(x_normed_attn,token_positions)
    x=residual_attn+attn_output

    residual_ff=x
    x_normed_ff=self.RMSNorm_FF(x)
    ff_output=self.Feed_Forward(x_normed_ff)
    x=residual_ff+ff_output

    return x
```

Structure of Full Transformer



- A Token Embedding module
- Several Transformer Block modules
- A RMSNorm module
- Final Linear Transformation module

Assembly of Complete Transformer

```
class Transformer_LM(nn.Module):
    def __init__(self,
                 d_model:int,
                 num_heads:int,
                 d_ff:int,
                 vocab_size:int,
                 num_layers:int,
                 max_seq_length:int=None,
                 theta:int=None,
                 dtype=None,
                 device=None):
        super(Transformer_LM,self).__init__()
        self.d_model=d_model
        self.num_heads=num_heads
        self.d_ff=d_ff
        self.vocab_size=vocab_size
        self.num_layers=num_layers
        self.max_seq_length=max_seq_length
        self.theta=theta
        self.dtype=dtype
        self.device=device
        self.embeddings=Generate_Embeddings(vocab_size,
                                            d_model,
                                            device=device,
                                            dtype=dtype)
```

```
self.transformer_blocks=nn.ModuleList([
    Transformer_Block(d_model=d_model,
                      num_heads=num_heads,
                      d_ff=d_ff,
                      max_seq_length=max_seq_length,
                      theta=theta,
                      dtype=dtype,
                      device=device)
    for _ in range(num_layers)
])
self.final_norm=RMSNorm(d_model,device=device,dtype=dtype)
self.final_layer=Linear_Transform(d_model,
                                  vocab_size,
                                  device=device,
                                  dtype=dtype)
```

Assembly of Complete Transformer

```
def forward(self,token_ids:torch.Tensor,token_positions:torch.Tensor)->torch.Tensor:
    x=self.embeddings(token_ids)
    for block in self.transformer_blocks:
        x=block(x,token_positions)
    x=self.final_norm(x)
    linear_score=self.final_layer(x)
    return linear_score
```